# Segmentation of ARX models through **SDP-relaxation techniques**

# Dario Piga and Roland Tóth

# Abstract

Segmentation of ARX models can be formulated as a combinatorial minimization problem in terms of the  $\ell_0$ -norm of the parameter variations and the  $\ell_2$ -loss of the prediction error. A typical approach to compute an approximate solution to such a problem is based on  $\ell_1$ -relaxation. Unfortunately, evaluation of the level of accuracy of the  $\ell_1$ -relaxation in approximating the optimal solution of the original combinatorial problem is not easy to accomplish. In this poster, an alternative approach is proposed which provides an attractive solution for the  $\ell_0$ -norm minimization problem associated with segmentation of ARX models.

## **SDP-relaxation**

Based on theory-of-moments relaxation [2], construct a sequence of SDP-relaxed problems to approximate the solution of the formulated polynomial optimization problem.

# **Problem description**

**Data-generating system:** 

 $y(k) = \phi^{\top}(k)\theta_{0}(k) + e(k)$ 

**Parameter estimation (with regularization):** 

 $\hat{\theta}_{N} = \arg\min \sum_{k=1}^{N} \left( u(k) - \phi^{\top}(k)\theta(k) \right)^{2} + \gamma \|\Delta\theta\|_{0}$ 

#### **Advantages:**

- Possibility to check if the global optimum of the original  $\ell_0$ norm minimization is attained by the constructed sequence of SDP-relaxed problems.
- Monotone convergence to the global optimum of the original  $\ell_0$ -norm minimization (no structural approximation).
- The peculiar structure of the formulated optimization problem can be used to reduce the computation complexity in solving the SDP-relaxed problems (computationally feasible).

# **Simulation results**

**Data-generating system:** 

 $y(k) + a_0(k)y(k-1) = b_0(k)u(k) + e(k)$ 

$$\begin{split} \sigma_N &= \arg \min_{\theta} \sum_{k=1}^{\infty} \left( g(k) - \psi^{-}(k) \sigma(k) \right) + \gamma \| \Delta \sigma \|_{0} \\ & \Delta \theta_k = \| \theta(k+1) - \theta(k) \|_{\infty} \end{split}$$

 $\ell_1$ -approximation [1]:

$$\hat{\theta}_N = \arg\min_{\theta} \sum_{k=1}^N \left( y(k) - \phi^\top(k) \theta(k) \right)^2 + \gamma \| \Delta \theta \|$$

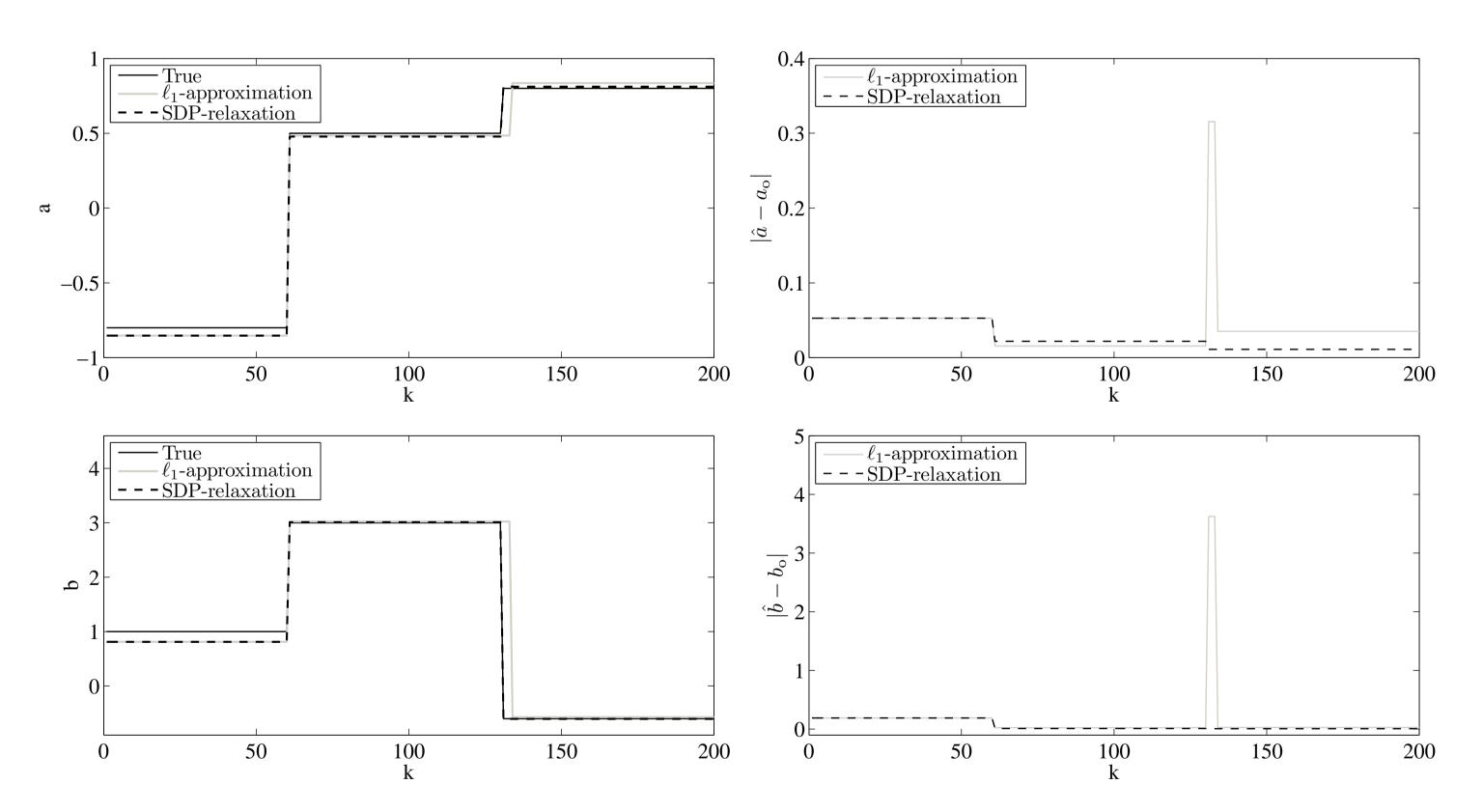
# **Polynomial formulation**

**Reformulation of**  $\ell_0$ **-norm minimization in terms of poly**nomial optimization:

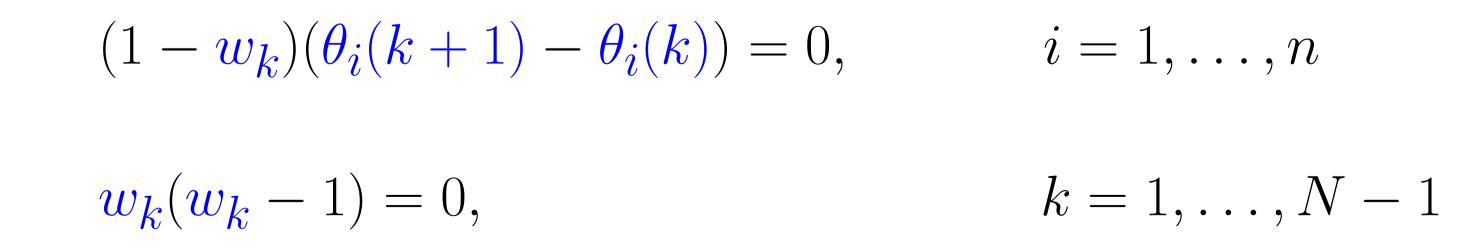
$$\min_{\substack{\boldsymbol{\theta}, \boldsymbol{w} \\ k=1}} \sum_{k=1}^{N} \left( y(k) - \phi(k)^{\top} \boldsymbol{\theta}(k) \right)^2 + \gamma \sum_{k=1}^{N-1} w_k$$
s.t.

### e(k) i.i.d., $e(k) \sim \mathcal{N}(0, 0.6^2)$

#### Results



# References



[1] H. Ohlsson, L. Ljung, S. Boyd, Segmentation of ARX-models using sum-of-norms regularization, Automatica, 46(6), 2010.

[2] J. Lasserre, Global optimization with polynomials and the problem of moments, SIAM Journal on Optimization, 11, 2001.



**Delft Center for Systems and Control** 

**Delft University of Technology**